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**RELATIONSHIPS BETWEEN MEASURES OF PHYSICAL FITNESS CHANGE WHEN
AGE DEPENDENT BIAS IS REMOVED IN A GROUP OF YOUNG MALE SOCCER
PLAYERS**

RUNNING HEAD: Age Independent Analyses of Physical Fitness

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children understand the fitness levels of the children at a particular point in time. The authors
have no conflicts of interest to declare.

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ABSTRACT

Age dependent bias is a key issue within talent identification of children, particularly when measures of physical fitness are used. Coaches in sport would benefit from a relatively straightforward method to remove age dependent bias, enabling identification of children who are relatively high performers for their age. This study aimed to determine whether removal of age effects caused changes in the relationships between physical performance and anthropometric measures commonly used in talent identification and development systems. Sixty male soccer players, aged 11 to 17 years, underwent measures of anthropometry, muscular power, strength, sprint speed, and agility. Most absolute measures of performance were significantly correlated with each other and all performance measures were significantly correlated with age. Age residuals were calculated, for all variables, to determine which players performed relatively well for their age and to investigate age-independent relationships between variables. In general, players with relatively fast sprint performance for their age were taller and had relatively high performance in jump power output and grip strength for their age ($r > 0.25$ and $P < 0.025$ in each case). Absolute sprint performance PC1 was significantly correlated with absolute agility performance PC1 ($r = 0.473$, $P < 0.001$). However, there was no significant relationship between age independent measures of agility and any other measures. Usage of age residuals highlights performers that have relatively high physical fitness for their age. Such analyses may assist the talent identification and development processes as long as differential rates of physical development between players are also considered.

KEY WORDS age, agility, growth, physical performance, sprint

INTRODUCTION

A key goal of national governing bodies and coaches in sport is to identify the athletes most likely to excel in the future (27, 38, 39). Such talent identification often measures physical fitness variables in children to determine those with the greatest potential. However, in sports where physical maturation is an advantage, athlete selection is skewed towards players with birth dates early in the playing year as older players are on average more physically mature (3, 11, 12, 14, 18, 25, 31, 32). This relative age effect may lead to early drop out in sport, with players born later in the selection year dropping out of soccer as early as 12 years old (11). Once athletes are selected, any differences between them and non-selected athletes are further compounded by access to higher quality training facilities and coaching (3). Such problems in talent identification can lead to many potential elite athletes having their opportunity for entry to talent development schemes delayed or denied.

Measures of physical fitness (e.g. muscular strength, speed, endurance and aerobic power) and anthropometrics (e.g. height, mass) have been found to correlate with higher performance in many sports (2, 8, 19, 30). Studies on soccer (association football) players have demonstrated that physical performance measures such as leg strength, agility and sprint performance are particularly useful in differentiating between elite and non-elite players (6, 15, 29) with agility and coordination of soccer players being especially high when compared to the general population (24, 28). Previous studies on team sports players have demonstrated significant correlations between different physical fitness measures such as straight line sprint, acceleration, agility and countermovement jump performances (17, 32, 40), however, it seems likely that at least some of these correlations are confounded by age related changes in performance, even when the age range of the players is as low as one or two years (20).

Improvement of talent identification in sport requires an understanding of the relationships between physical performance measures and how these relationships alter with age. This is particularly important in sports such as soccer where older players tend to be preferentially selected, most likely due to their greater physical performance that is considered to be an advantage in such sports. Therefore, it would be useful for coaches and managers of sports teams to be provided with a relatively straightforward means to analyse physical performance data to determine which children had relatively high performance for their precise age. Such an approach could improve current talent identification programmes by reducing age dependent bias.

The aims of the present study were to investigate the relationships between various physical performance measures in young soccer players and to consider the effect of using age residuals (age independent measures) on these relationships. We were particularly interested in demonstrating how coaches could account for age in analyses of standard anthropometric and physical performance variables typically used in talent identification in soccer. We hypothesised that: 1) measures of physical fitness, such as sprint, agility, jump and grip strength performance, would improve with age; 2) that relationships between indices of physical fitness might change once the effects of age were removed.

METHODS

Experimental Approach to the Problem

To highlight the application of our approach to coaches we used standard, field based, anthropometric and physical fitness tests to provide data indicative of that which is often collected and used in an applied environment, such as within soccer talent identification programmes. All soccer players were recruited from one provider of soccer coaching for children, Coerver Coaching UK. Data was analysed in absolute form to replicate previous published studies and the approach currently used in talent ID programmes. However, many previously published studies have demonstrated that a relative age effect exists in talent identification programmes, such that older participants in each age group tend to be preferentially selected as their physical performance is high for the range of ages they are compared to. Therefore, data in the present study was further analysed to determine the relationships between age and the anthropometric and physical fitness data to generate a new set of performance data that gave a score to each individual with respect to how well they performed for their precise age. Further correlational analyses were undertaken to demonstrate how accounting for age altered the relationships between performance measures as the age effect is a confounding factor in performance analysis. This approach was used to demonstrate how age dependent bias could be removed from typical physical fitness data in talent ID programmes to increase the likelihood that talent ID focuses on those individuals with the best long term potential.

Subjects

Participants and parents/guardians were informed of the benefits and risks of the investigation prior to parents/guardians signing an institutionally approved informed consent document to participate in the study. This study received institutional ethics committee approval. Sixty

male soccer players, of varied training and competition status, aged between 11 and 17 years old (mean \pm *SD*: 13.8 \pm 1.3 years, height 1.56 \pm 0.10 m; body mass 47.4 \pm 8.8 kg) participated in this study. The age of each participant on the day of testing was calculated, to two decimal places, from their date of birth. Data was collected during normal coaching sessions at the normal coaching venue, in the presence of investigators, Criminal Records Bureau checked coaches, other soccer players and their parents. All soccer players wore full soccer kit and were individually verbally encouraged to undertake maximal exertion during testing.

Procedures

All indoor performance tests took place between 17.00 and 19.00. Height (to the nearest mm) and body mass (to the nearest 0.1 kg), of each player, were recorded, whilst barefoot in their soccer kit, using a standard stadiometer and weighing scales (Seca Instruments, Germany) respectively. Maximum forearm girth, indicative of overall muscle mass, (1, 22) was measured to the nearest 0.1 mm using a standard anthropometric measuring tape (mean \pm *SD*: 22.5 \pm 1.8 cm). Triceps and calf skinfold thicknesses were measured to the nearest 0.1 mm (mean \pm *SD*: 12.2 \pm 5.3 and 11.5 \pm 4.9 mm respectively) using skinfold callipers (Harpender, UK) in accordance with ISAK guidelines. Skinfold measurements were repeated three times and the median value was used for further analyses.

Each participant undertook the following tests indoors on a sprung wooden floor: countermovement jump, to estimate power production of the lower limbs, (33) and hand-grip strength, to indicate body strength, (41).

The counter movement jump technique was demonstrated to each participant immediately prior to the participant undertaking three practice jumps (36). In brief, a jump consisted of a continuous series of movements involving leg flexion into a squat position prior to leg extension, whilst using the arms during one continuous movement, to jump as high as possible into the air. Three counter movement jumps were then performed on a jump mat (Globus, UK) with a 3-5 second intermission between each jump. The jump mat system calculated jump height from the recorded flight time of the jump. Jump height was recorded for each jump, with the highest performance for each participant used in subsequent analyses (mean \pm *SD*: 0.32 \pm 0.06 m). Jump power output (W) was calculated from jump height according to Harman and co-workers (mean \pm *SD*: 58.9 \pm 13.1 W (10)).

The hand-grip strength test was demonstrated to each participant. Participants held a hand-grip dynamometer (Takei Hand-Grip Dynamometer, Fitness assist, UK) that was adjusted according to individual hand size, so that the back rested in the heel of the palm and the handle rested in the middle of the four fingers of the participant to facilitate a comfortable grip. Participants raised their extended arm to a vertical position and then, over a 5 second time period, lowered their arm to their side whilst maximally squeezing the dynamometer. This technique ensured an optimal arm reach and shoulder angle to elicit a maximum grip strength measure (16). Each participant performed one practice attempt with each hand and then performed this test 3 times with each hand. The highest overall performance, to the nearest 1.0 kg, for each participant, was used in subsequent analysis (mean \pm *SD*: 29 \pm 7 kg).

All outdoor performance tests took place between 19.00 and 21.00. A standard outdoor 10 minute warm up was given by the Head Coach of the soccer academy, which included

jogging, running and stretching on a synthetic 3G Astroturf pitch prior to the outdoor tests. A 30 m straight line sprint test and an agility T-test were conducted outdoors on a synthetic 3G Astroturf pitch.

Players sprinted over a 30 m course (35) in a straight line with split times recorded to the nearest 0.001 s for 5, 15 and 30 meters using a light gate system (SmartSpeed, UK). The start line was set up 0.5 m behind the first set of timing gates. Four courses were set up in parallel, such that 4 players ran simultaneously alongside each other with each participant individually verbally encouraged to maximise their performance throughout the 30 m sprint. At the end of each sprint each participant jogged back to the start and waited for approximately 3 minutes before their next attempt. Each participant performed three sprints and the fastest performance was used in subsequent analyses (mean \pm SD: 4.94 \pm 0.38 s for 30m sprint).

Each participant walked through a modified agility T-test (13) with instructions from the researcher to clarify the test procedure. The T-test consisted of: a forward sprint from a standing start over 10 meters, with sprint time measured between 0 m and 5 m; then 5 m sideways movement to the left; then 10m sideways movement to the right; then 5 m sideways movement to the left, to a central point; then 5 m sprint backwards, with overall time measured for this 'T' section of the test i.e. after the first 5 m to before the last 5 m of the test; then a 5 m meter sprint forwards to the finish, with sprint time measured for this final 5 m.

Each of the three sections, initial 5 m sprint, T section and final 5 m sprint, was timed to the nearest 0.001 s by a light gate system (Smartspeed, UK). The T-test course was marked with cones and each participant was individually verbally guided through the course during each attempt. Four courses were set up in parallel, such that 4 players ran simultaneously alongside each other with each participant separately verbally encouraged to maximise their

performance throughout the T-test. At the end of the T-test each participant waited for 5 minutes before their next attempt. Each participant performed three T-tests, with their maximal performance used in subsequent analysis (mean \pm SD: 11.5 \pm 1.3 s; total for whole T-test). Any player who crossed one foot in front of the other during the sideways movement or whose foot did not cross the cone at either end of the 'T' had that attempt at the T-test deleted from their performances.

Statistical Analyses

All performance and anthropometric variables were found to be significantly correlated with age. Therefore, unstandardised age residuals were calculated for all variables. Using unstandardised age residuals removed age as a confounding factor, assigning a new 'score' to each participant according to whether they were relatively better or worse than the performance that would be predicted, from the regression relationship, for their age (7). Using grip strength as an example, those individuals who correspond to data points above the regression line in Figure 1 had positive age residual 'scores', reflecting better performance for their age than would be predicted from the regression line fitted to that group of individuals; the further the data point was above the regression line the greater the age residual 'score'.

Insert Figure 1 about here

Each of the subsequent analyses were undertaken on absolute values, then repeated on age residuals, to allow us to compare the relationships found between absolute performance values with the relationships found between those same performance measures when any

confounding effects of age had been removed. This approach enabled us to determine whether age related bias occurred in our data sets.

Similar performance measures were grouped together as: anthropometrics (body mass, height, maximum forearm girth, triceps skinfold, calf skinfold); sprint times (first 5 m, first 15 m, 5 m to 15 m, last 15 m); T-test times (first 5 m, T, last 5 m). Jump power output and grip strength were kept as separate variables in all further analyses. Regression analysis of each group of variables (anthropometrics, sprint times, agility times) revealed that variable inflation factor values ranged between 1.43 and 43.9 suggesting that for most variables multicollinearity is a problem; i.e. effectively each variable within a group (e.g. anthropometric measures) was significantly correlated with other variables within the same group such that they could not be considered as independent variables (7). Principal component (PC) analysis was used, as described below, to reduce the number of variables in each group of measurements (anthropometrics, sprint times, agility times) and to avoid problems of collinearity within such groups of data (7); i.e. instead of using lots of variables which were correlated with each other (e.g. the times taken to complete different sprint distances) we converted those variables to their principal components such that each principal component for a group of variables was not correlated with the other principal components found to describe that same group of variables. Prior to principal component analysis, each variable was scaled such that its data ranged between -1 and +1 to prevent the differing magnitude of each performance or anthropometric measurement within a group of measurements affecting subsequent principal component analyses. Such scaling does not affect the relative variation between individuals within each data set. The Anderson-Rubin extraction method was used to extract a 'score' for each individual, for each principal component with an eigenvalue > 1 . The Anderson-Rubin method produces uncorrelated

principal components within each group of data such that the variables used in the principal component analysis have different weightings in each principal component (7, see below for examples).

Insert Table 1 about here

One principal component was extracted for the sprint group of absolute data, explaining 92% of the inter-individual variation in the absolute sprint data, and one for the age independent sprint data, explaining 83.5% of the inter-individual variation in the age independent sprint data. Further consideration of each sprint PC1 revealed high positive loading scores for all sprint measurements made, >0.84 in each case, of a possible maximum value of 1.0 (Table 1); i.e. variation in sprint PC1 was highly influenced by variation in performance over all sprint distances measured, such that sprint PC1 could be used as a single variable that reliably represented the variation in sprint performance between individual participants over all distances measured. One principal component was extracted for the agility T-test group of absolute data, explaining 90% of the inter-individual variation in the absolute agility data, and one principal component was extracted for the age independent T-test data, explaining 83.3% of the inter-individual variation in the age independent agility data. Further consideration of each agility PC1 revealed high positive loading scores for all agility T-test measurements made, >0.89 in each case (Table 2); i.e. variation in agility PC1 was highly influenced by variation in performance over all agility distances measured. Two principal components were extracted for the anthropometrics group of absolute data, with the first component explaining 60% of the inter-individual variation in that group of data and the combination of the two components explaining 91% of the variation in anthropometric data. Two principal components were extracted for age independent anthropometrics data, with the

first component explaining 64% of the inter-individual variation in that group of data and the combination of the two components explaining 86.7% of the variation in anthropometric data. Consideration of absolute and age independent anthropometric principal components revealed that: PC1 had high positive loading scores, > 0.61 in each case (Table 3) for all measures except height, but that loadings were especially high and positive for measures of body mass and maximum forearm girth, >0.91 in each case, i.e. anthropometric PC1 was particularly influenced by changes in body mass and maximum forearm girth such that high values in this anthropometric measure reflected high body mass and high forearm girth; absolute PC2 had a high negative loading for height, -0.721 , and a high positive loading for triceps skin fold, whereas age independent PC2 had a high positive loading for height, 0.735 .

Insert Tables 2 and 3 about here

One tailed Pearson's product moment correlation was used to investigate the relationships, in both absolute and age independent data sets (7): between PC1 of sprint performance and PC1 of agility T-test performance; between PC1 of sprint data, or between PC1 of agility T-test data, and all other data sets (PC1 and PC2 of anthropometric data; grip strength data; jump power output data); i.e. grip strength data and jump power output data were considered as variables in their own right, unlike the groups of sprint, agility, anthropometric data that had been analysed to generate principal components. An r value of: >0.5 (or <-0.5) was considered as large (strong); between 0.5 and 0.3 , or -0.5 to -0.3 as moderate; 0.3 to 0.1 , or -0.3 to -0.1 , as small; and 0.1 to -0.1 trivial (5). Whenever a principal component was found to be correlated, then the loading scores of each performance variable within that principal component were considered, to enable determination of which performance variables had the greatest influence on that principal component. Loading scores within each PC of: > 0.6 , or $<$

-0.6, were interpreted as high loading, having a large effect on the principal component; 0.4 to 0.59, or -0.4 to -0.59, were interpreted as medium loading; between -0.4 and 0.4 as low loading (9). A factor loading score > 0.7 or < -0.7 was considered as a significant loading as $n = 60$ (9).

Stepwise analysis of independent variables, using multiple linear regression, was used to determine which of the measured variables were possible predictors of age independent sprint performance and age independent agility performance (7). Independent variables were only included in the model if they were judged to have a significant effect on the model, when the probability of the F value for the model was less than 0.05 (7). The r^2 value, adjusted as a population estimate, of each model was used to indicate the percentage of variation in sprint or agility performance explained by the model. The significance of each model was assessed using a two-tailed ANOVA.

The truncated product method (42) was used to combine all the P values in this study to determine whether there was a bias from multiple hypothesis testing. The truncated product method P value was < 0.001 , suggesting that the results were not biased.

Significance was taken at the level of $P < 0.05$.

RESULTS

Variation in Absolute Performance

When absolute performance values were considered there was a significant moderate relationship between sprint performance PC1 and agility performance PC1 ($r = 0.473$, $P < 0.001$). In general those with faster sprint times, over any distance tested, were quicker in any section of the agility T-test. For example for sprint performance over 5m there was a significant moderate correlation with agility performance in the T section of the T-test (Figure 2; $r = 0.446$, $P < 0.001$). Variation in both sprint and agility performances were significantly correlated with variation in age, with strong correlations in each case such that older players were, in general, faster in sprint (lower sprint times), e.g. sprint 5m $r^2 = -0.662$, $P < 0.001$, and agility tests (lower agility times), e.g. agility T section $r^2 = -0.616$, $P < 0.001$. Essentially 44% of the variation in performance between players in the first 5m of the sprint test and 38% of the variation between players in the T section of the T-test could be predicted by variation in age.

Insert Figure 2 about here

Insert Table 4 about here

Absolute sprint times (PC1) were significantly strongly positively correlated with anthropometrics PC2 ($r = 0.782$, $P < 0.001$ (the key influencing factor in this component was negative loading for height)) and were significantly strongly negatively correlated with jump power output ($r = -0.585$, $P < 0.001$) and grip strength ($r = -0.734$, $P < 0.001$) (Table 4) i.e. soccer players who were faster at sprinting tended to be taller, (as height is the main variable affecting absolute anthropometric PC2 and is negatively loaded within PC2; Table 3), with higher jump power output and greater grip strength. There was a significant, but small,

negative correlation between absolute agility times PC1 and anthropometrics PC1 ($r = -0.262$, $P = 0.043$ (the key influencing factors in this principal component were positive loadings for body mass, forearm girth, tricep and calf skinfold measurements, along with significant, moderate negative correlations between agility times (PC1)) and jump power output ($r = -0.400$, $P = 0.002$) and grip strength ($r = -0.401$, $P = 0.001$) (Table 4). However, there was a significant moderate positive correlation between agility times PC1 and anthropometrics PC2 ($r = 0.326$, $P = 0.011$); i.e. soccer players who were faster at the agility T-test tended to be taller, thinner and lighter with higher jump power output and greater grip strength.

Age-Independent Variation in Performance

Analysis of principal components of age residuals was performed to determine the relationships between performance measures independently of the effects of age and collinearity (the effects of related independent variables being highly correlated e.g. correlation between times over different sprint distances). There was no significant relationship between sprint PC1 (age independent) and agility PC1 (age independent) (Figure 3; $r = 0.069$, $P = 0.30$). Therefore, players who performed well for their age on the sprint test did not necessarily perform well for their age on the agility T-test, and vice versa. Therefore, performance in the agility T-test could not be predicted by performance in the sprint test once the effects of age were removed. In fact age independent agility times PC1 was not significantly correlated with any other performance variables (Table 5).

Insert Figure 3 about here

Insert Table 5 about here

Soccer players with relatively fast sprint performance (sprint PC1), low sprint times, for their age also had relatively high jump power output (Figure 4; Table 5; $r = -0.291$ [small], $P = 0.012$), grip strength (Figure 5; Table 5; $r = -0.452$ [moderate], $P < 0.001$) and anthropometrics PC2 score (Figure 6; Table 5; $r = -0.508$ [strong], $P < 0.001$) for their age. Therefore, in general, soccer players who were relatively tall, strong and powerful for their age had faster sprint times. Stepwise multiple linear regression analysis determined that 25% of the age independent variation in sprint performance was best explained by age independent variation in anthropometrics PC2 (ANOVA $F_{1,58} = 20.2$, $P < 0.001$ (primarily due to the effect of height, as this had the greatest effect on anthropometrics PC2 as indicated in Table 3)). Therefore, the key age independent predictor of faster sprint performance was being taller.

Insert Figure 4 about here

Insert Figure 5 about here

Insert Figure 6 about here

Discussion

All performance and anthropometric variables measured in this study were found to be significantly correlated with age in accordance with hypothesis one. In general, older soccer players were taller and heavier and had higher sprint, strength and agility performance. Previous studies have also demonstrated that such anthropometric and physical fitness measures change with age in children (4, 21, 26, 32). Cobley et al (4) demonstrated wider variation in player performance across a 2 year age range than across a one year age range, however as discussed below we have illustrated ways in which either the effect of age can be excluded or the performance of the player can be visualised according to their precise age.

As each variable is significantly affected by age, then age becomes a confounding variable for any analysis of player performance. When absolute performance values of physical fitness were considered, in the present study, most variables were significantly correlated (low to strong) with each other across this age range of 11 to 17 year old soccer players (e.g. Table 4). Previous studies have also found significant low to medium correlations between absolute values of different physical fitness measures including agility, sprint and countermovement jump performance (17, 23, 34), with some finding high correlations (40). However, in many studies even small differences in age between participants may mask the true relationships between such physical fitness measurements.

One way to deal with the confounding effect of age is to look at variation in player performance that is independent of age by converting each player's performance to an age residual score that essentially indicates how much better or worse that player has performed, for their precise age, than would have been predicted from the whole data set of participants. Analysis of age residuals altered many of the relationships between performance variables, in

accordance with hypothesis two, highlighting which performers had relatively high physical fitness for their age. Once age residuals (age independent performance measures) were considered there was no correlation between sprint and agility performance (Figure 3). Good agility performance requires rapid direction changes, therefore involving high acceleration rates. Using age residuals we found that sprint performance was significantly correlated with anthropometrics PC2 (largely influenced by height), but agility performance was not. We found that analysis of absolute measures of performance suggested that soccer players who were faster at the agility T-test tended to be taller, thinner and lighter in mass with higher jump power output and greater grip strength. However, age-independent agility performance was not correlated with any other variable measured in this study, highlighting that the correlations between absolute agility and other absolute performance and anthropometric measures were actually due to each measure being highly correlated with age rather than any intrinsic relationship between agility and the other measures. In contrast analysis of age-independent sprint performance had less effect on the relationships between sprint and other performances, such that soccer players who were relatively fast sprinters for their age also tended to be relatively tall, strong and powerful. However, multiple regression analysis indicated that the key variable affecting sprint performance, in our age independent analyses, was height suggesting that differing rates of maturation could have influenced variation in sprint performance between individuals.

Limitations

We did not attempt to determine the maturity status of the participants in this study. Whilst we corrected for chronological age we made no attempt to differentiate between the effects of growth and maturation on physical performance. Our findings do indicate that those participants who were tall for their age had relatively fast sprint performance for their age.

Previous studies have demonstrated that maturity status affects physical performance (17, 20, 21, 37). Future work could use skeletal age, such as measurement of hand-wrist radiographs, as a measure of maturity (biological age; 17) to compare the utility of skeletal age independent measures of performance with the age independent measures used in the present study. Future work could also include aerobic performance measures in such a study to consider the effects of age and maturation on performance. We did not account for training status or competition background in the present study, however in practical applications of an approach such as ours the coach would use a knowledge of the training and competition status of each individual within their interpretation of such data.

Therefore, we suggest that age residuals of performance variables should be used, preferably with associated objective assessment of maturity, within talent identification and development processes over prolonged time periods such that the impact of changes in rates of physical development of athletes and variation in training and competition status can be accounted for. For example, when comparing two children of the same age, one child might develop relatively rapidly such that they are taller and have higher muscle mass at a particular time point causing their sprint performance to be much higher; however, careful monitoring of performance and anthropometric measures of individuals within a squad or team over time would highlight such issues and allow the coach or manager to make informed decisions based on these measures and a knowledge of their training status (4). Whilst usage of age residuals of performance measures might not guarantee that a team or squad was composed of the athletes with the highest physical fitness at any one time, it might better equip the squad for longer term development by helping to remove the current age bias in talent ID and selection processes.

PRACTICAL APPLICATIONS

Usage of age residuals may prove a useful tool within talent identification and talent development processes, allowing a relatively simple way to determine which athletes are performing particularly well for their age. Such an approach would reduce some of the existing problems of age bias, the relative age effect, and resultant drop-out caused by current talent identification systems (3, 11, 12, 25, 31, 32). Alternatively, a more simplistic approach, would be to plot a physical performance measure against precise age and fit a 1st order regression line to the data, assuming that there is a significant relationship between the performance variable and age; then any individual whose data point is above the line has performed relatively well for their age when compared against the typical performance of individuals in that group (Figure 1) and may be suitable for consideration for a higher level team or squad or for more focused developmental support.

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Table 1. Loading scores from principal component analysis of sprint test measurements demonstrated that for both absolute and age independent analyses one principal component could explain most of the variation in sprint performance for each distance measured.

Principal component	First 5 m	First15 m	From 5 m to 15 m	Last 15 m
PC1 (3.70) absolute	0.927	0.992	0.957	0.955
PC1 (3.34) Age independent	0.846	0.984	0.908	0.911

The eigenvalue is given in brackets for each principal component (PC). The first principal component is shown for analysis of absolute sprint measurements and also for analysis of age independent sprint measurements. The closer the loading score is to 1.0 the greater the influence that variable has on the principal component.

Table 2. Loading scores from principal component analysis of agility T-test measurements demonstrated that for both absolute and age independent analyses one principal component could explain most of the variation in agility performance for each distance measured.

Principal component	First 5 m	After first 5 m to before last 5 m	Last 5 m
PC1 (2.70) absolute	0.949	0.940	0.958
PC1 (2.50) age independent	0.914	0.892	0.932

The eigenvalue is given in brackets for each principal component (PC). The first principal component is shown for analysis of absolute agility T-test measurements and also for analysis of age independent agility T-test measurements. The closer the loading score is to 1.0 the greater the influence that variable has on the principal component.

Table 3. Loading scores from principal component analysis of anthropometrics measurements demonstrated that for both absolute and age independent analyses a combination of two principal components could explain most of the variation in anthropometric measures.

Principal component	Height	Body mass	Tricep skin fold	Calf skin fold	Maximum forearm girth
PC1 (3.00) absolute	0.599	0.922	0.616	0.736	0.933
PC2 (1.60) absolute	-0.721	-0.309	0.731	0.607	-0.193
PC1 (3.21) age independent	0.540	0.916	0.741	0.828	0.917
PC2 (1.13) age independent	0.735	0.241	-0.566	-0.430	0.172

The eigenvalue is given in brackets for each principal component (PC). The first two principal components are shown for analysis of absolute anthropometrics measurements and also for analysis of age independent anthropometrics measurements. The closer the loading score is to 1.0 or -1.0 the greater the influence that variable has on the principal component.

Table 4. Pearson product moment correlation matrix for absolute sprint times, agility times and other performance measurements.

	Anthropometrics PC1	Anthropometrics PC2	Jump power	Grip strength
Sprint times PC1	-0.063 <i>0.635</i>	0.782* <i>< 0.001</i>	-0.585* <i>< 0.001</i>	-0.734* <i>< 0.001</i>
Agility times PC1	-0.262* <i>0.043</i>	0.326* <i>0.011</i>	-0.400* <i>0.002</i>	-0.401* <i>0.001</i>

Values are r values, with corresponding P values underneath in italics, $n = 60$ in each case.

*denotes $P < 0.05$. PC=principal component.

Table 5. Pearson product moment correlation matrix for age independent sprint times, agility times and other performance measurements.

	Anthropometrics PC1	Anthropometrics PC2	Jump power	Grip strength
Sprint times PC1	0.103 <i>0.217</i>	-0.508* <i>< 0.001</i>	-0.291* <i>0.012</i>	-0.452* <i>< 0.001</i>
Agility times PC1	-0.211 <i>0.053</i>	0.100 <i>0.224</i>	-0.091 <i>0.245</i>	0.026 <i>0.423</i>

Values are r values, with corresponding P values underneath in italics, $n = 60$ in each case.

*denotes $P < 0.05$. All measures used in this analysis were age independent. PC=principal component.

Figure 1: Absolute grip strength was significantly correlated with age (Pearson $r = 0.706$, $P < 0.001$, $n = 60$) such that older players tended to have higher strength.

Figure 2: Absolute sprint and agility performance were significantly correlated (Pearson $r = 0.446$, $P < 0.001$, $n = 60$). Generally those soccer players with faster sprint times were also quicker in the agility T-test.

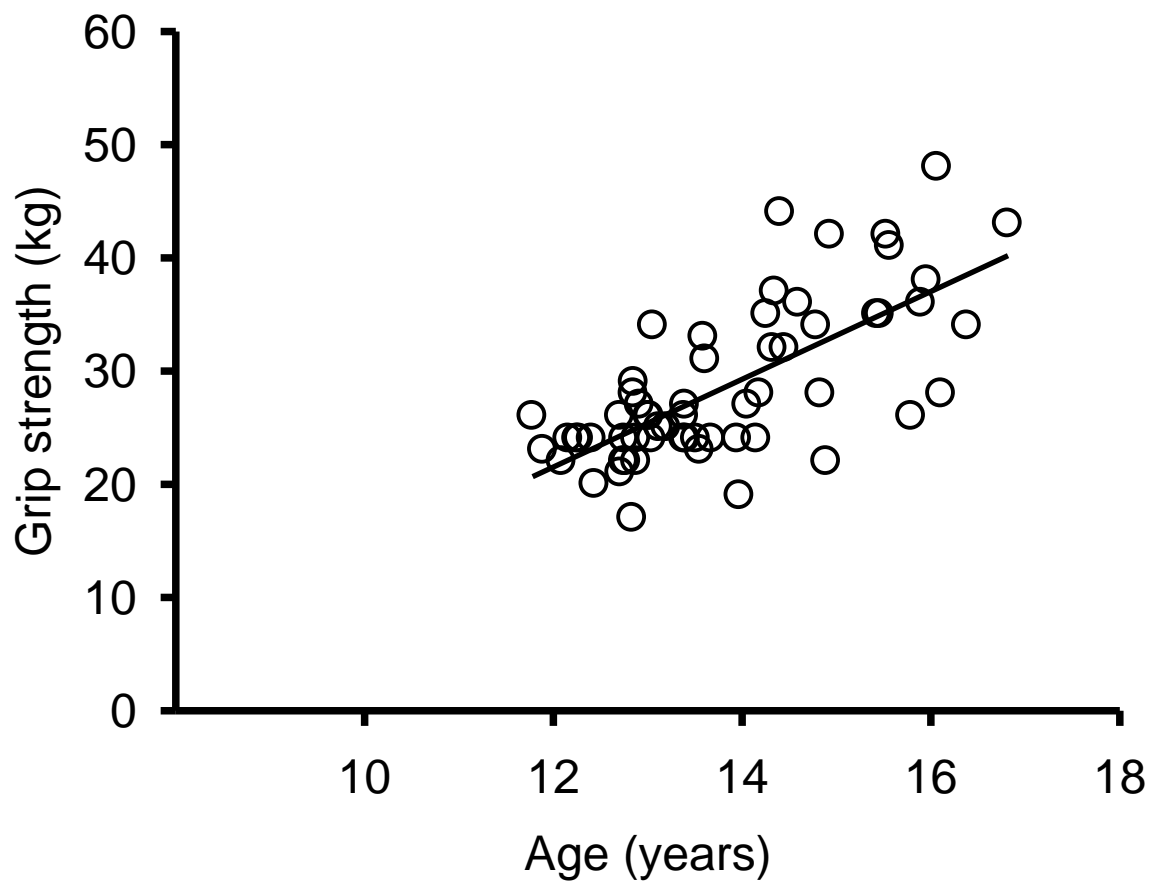
Figure 3: There was no significant correlation between sprint performance and agility when principal components of age residuals were analysed (Pearson $r = 0.069$, $P = 0.30$, $n = 60$). Therefore, soccer players who were relatively good for their age at the sprint test were not necessarily relatively good for their age at the agility T-test, and vice versa. PC=principal component.

Figure 4: Sprint performance PC1 was significantly correlated with jump power output when age residuals were analysed (Pearson $r = -0.291$, $P = 0.012$, $n = 60$). Soccer players with relatively fast (low) sprint times for their age usually had relatively high jump power output for their age. PC=principal component.

Figure 5: Sprint performance PC1 was significantly correlated with grip strength when age residuals were analysed (Pearson $r = -0.452$, $P < 0.001$, $n = 60$). Stronger individuals for their age were usually faster sprinters for their age. PC=principal component.

Figure 6: Sprint performance PC1 was significantly correlated with anthropometrics PC2 (Pearson $r = -0.508$, $P < 0.001$, $n = 60$). This suggests that taller individuals for their age were usually faster sprinters for their age.

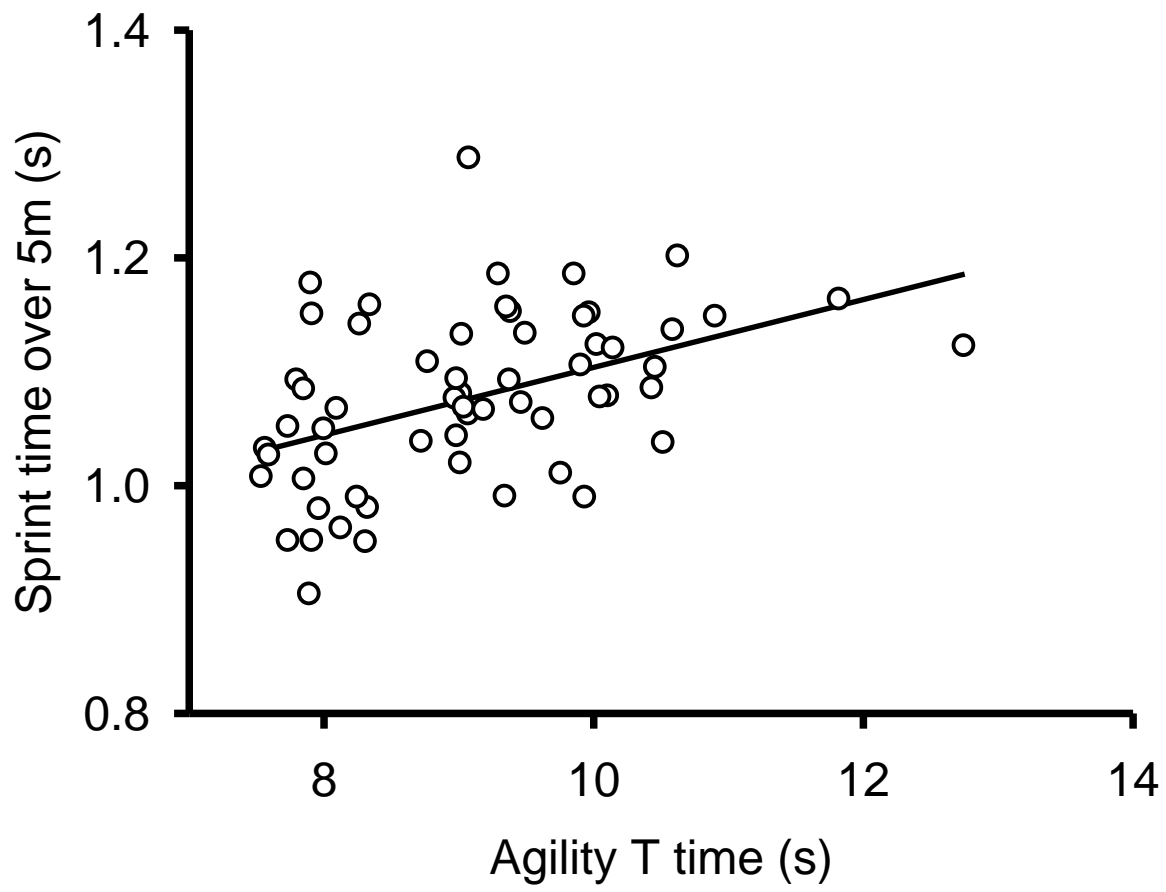
637 Figure 1



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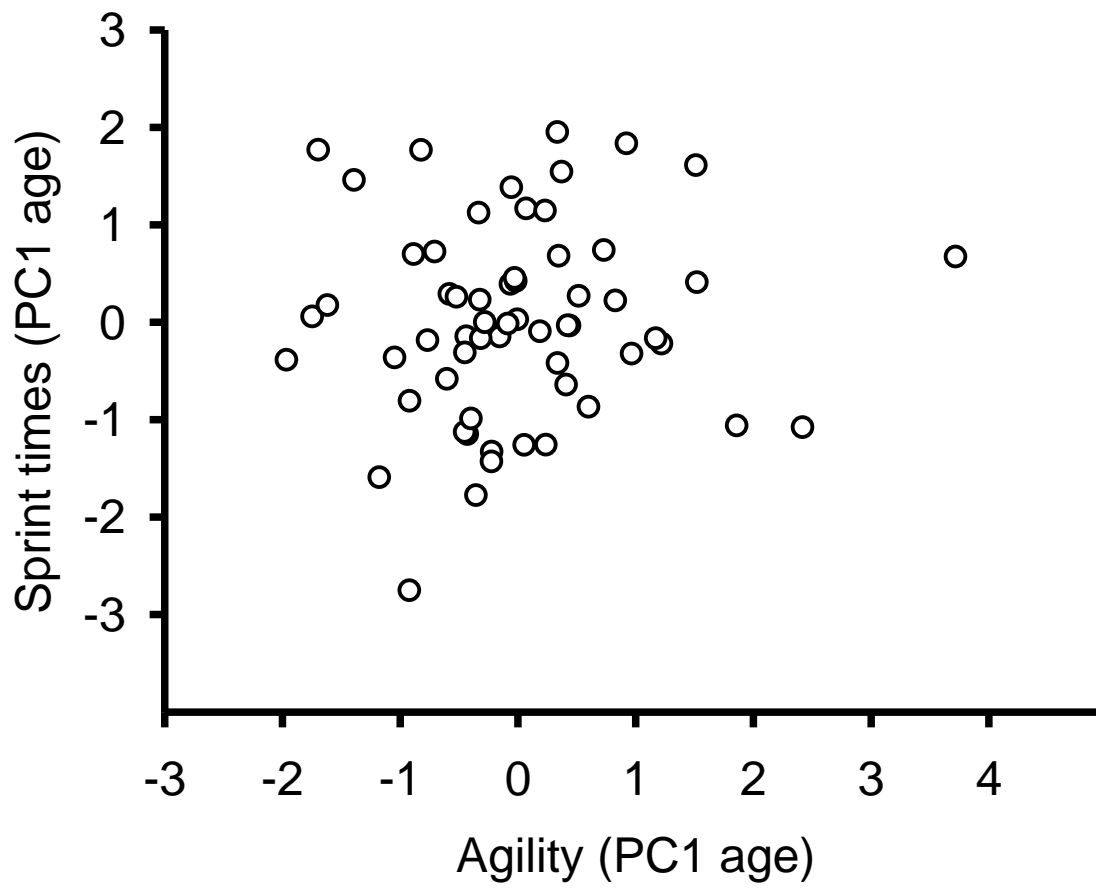
640 Figure 2



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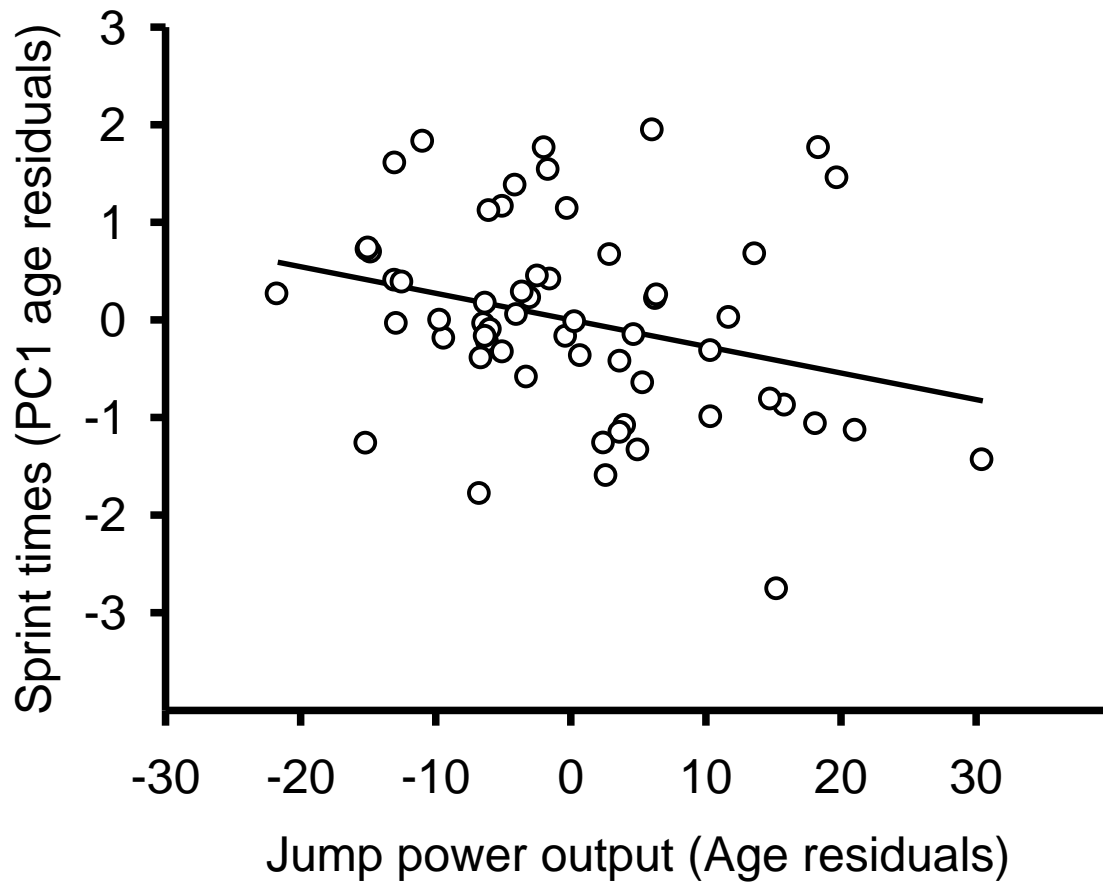
643 Figure 3



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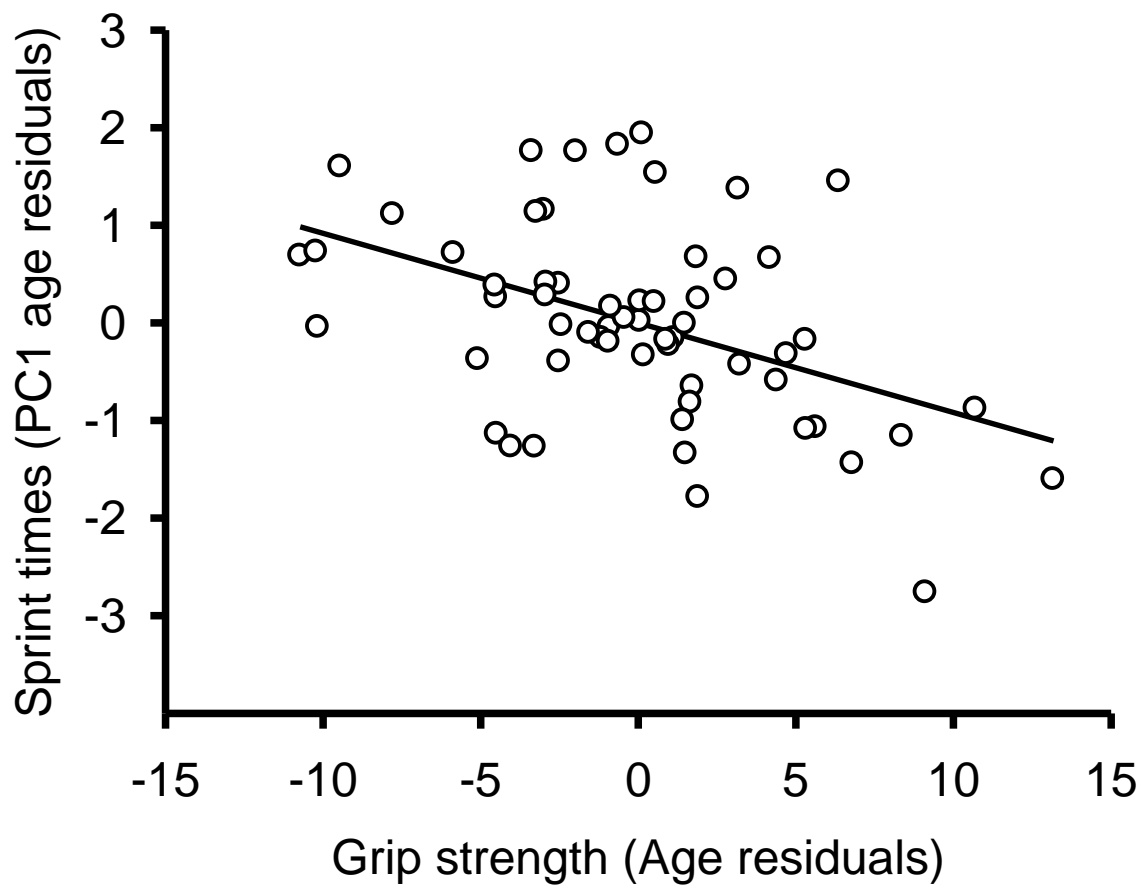
646 Figure 4



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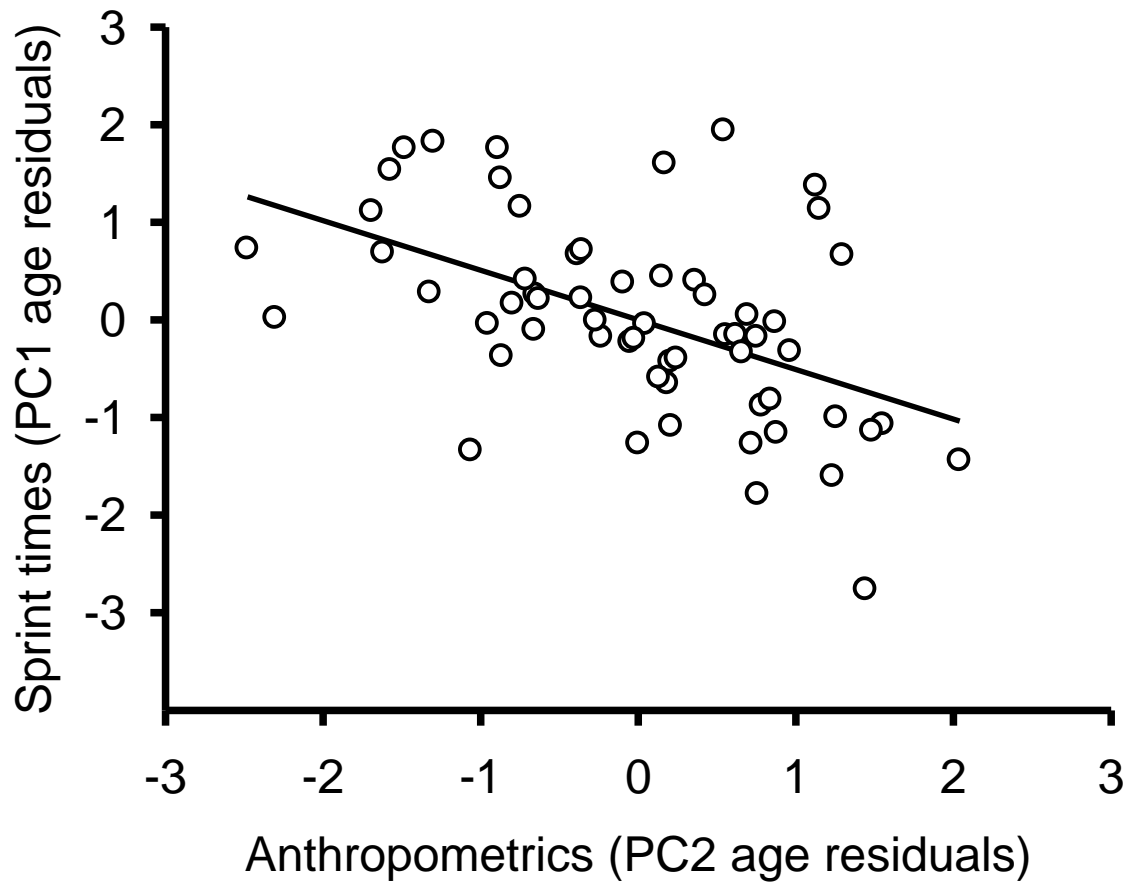
649 Figure 5



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652 Figure 6



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